A Federated Learning Approach to Predicting Communication Demand in the National Airspace

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Overview

- Background
- Demand Prediction Framework – needs and high-level phases
- Workload modelling
  - Data Sources
  - Models and Aspects – aggregate, discrete, relational
- Parameter Inferencing
  - Scope and Data Sources
  - Predictive / Prescriptive approaches

Background

- Aviation consumes ~14% of US spectrum, regulatory and tech. pressures to reduce
- Autonomous spectrum project is transformative, decades-ahead, may inform policy
  - Machine learning approaches require quality data items, such as communication demand
- Communication technologies may continue to evolve
  - Continued transition of voice -> VDL clearance requests
  - ICAO regulations include Sub-channelization (25 -> 8.33 kHz spacing)
- Nature of communication services will expand and alter
  - Medium altering: digitization, sub-channelization….
  - Expansion: UAS/UAM/AAM data and control plane services
- Demand prediction research primarily addresses time-series forecasting

Comm Demand should be generalized, to allow for robust and speculative approaches to NAS comms

Demand Prediction Framework

Defining requirements based on an Autonomous Spectrum Concept

Relevant challenges/constraints for comm demand prediction

- **Data engineering:** What will make data sufficient? ATC Workload Modelling
- **Technology Implementation Independence & Backwards Compatibility:** How do we support both in demand prediction? Modular, event-oriented predictions
- **System resiliency:** How can we insure prediction accounts for outages? NOTAM and convective weather information

- ATC Elements
  - National Flow Control (ATCSCC)
    - Define Frequency re-use factor and bands available to each region
  - En-route / Regional Control (ARTCC)
    - Predicts regional air traffic
    - Allocates channel set from ATCSCC recommendation
  - Airport (ATCT) & Departure / Arrival (TRACON) Control
    - Refined predictions with real-time trajectory and flight information
    - Joint channel-power allocation from ARTCC candidate channels

Additional Requirements

- Data are distributed across large domains
  -> federated learning necessary to generalize
  - Hierarchical design necessary: training overhead v. accuracy
- Workload data are non-IID
  -> data aggregation similar to Astraea Framework
- Trends currently require a mix of data & embedded, sector-specific features -> personalization is necessary
- Degree of explainability desirable, if possible

Data Investigation

Framed with Air Traffic Control Workloads

- Horizontal Movement: baseline workload
  - sector density
  - transit time
- Conflict Detect-and-Resolve: maintaining minimum separation
  - Type: succeeding, crossing opposite,
  - Phase: climbing, cruising, descending
- Coordination: non-conflict events requiring coordination
  - clearance issue, tower / facility / silent transfer
- Aircraft Maneuvering: mitigating external factors
  - level off, commence climb/descent

Relevant Sherlock Data Items

Dataset	Summary	Workload Sufficiency
IFF Data	Flight plan amendments, re-broadcasts, and flight track information	**Coordination:** re-broadcasts indicate sector crossings **Conflict detection:** amendments **Aircraft maneuvering:** amendments
EV Data	Flight events in terms of airspace operations: Takeoff/landing, top-of-climb/descent, sector crossing, go-around, etc.	**Aircraft Maneuvering:** Altitude changes described in-detail **Coordination:** sector crossings **Conflict Detection:** go-arounds and altitude changes
Instant Aircraft Counts	Sector aircraft counts over 15-minute windows: Min, max, average, aggregate	**Horizontal Movement:** sector density
Sector Statistics	Daily statistics of each sector: Total aircraft count, hourly flow, Average transit time and airspeed, Sector transition counts	**Horizontal Movement:** average transit time, density statistics **Coordination:** Sector transition counts
NOTAMs	Urgent, non-standard conflicts and airspace outage notices	**Conflict Detection:** indication of reduced sector / center capacity
CWAM	Describes regions with high probability of convective weather (60/70/80%)	**Aircraft Maneuvering:** adjusted airflows from convective weather
Echo Top	Radar measurements of cloud height, corresponds to weather severity	**Aircraft Maneuvering:** adjusted airflows from convective weather

Event Prediction

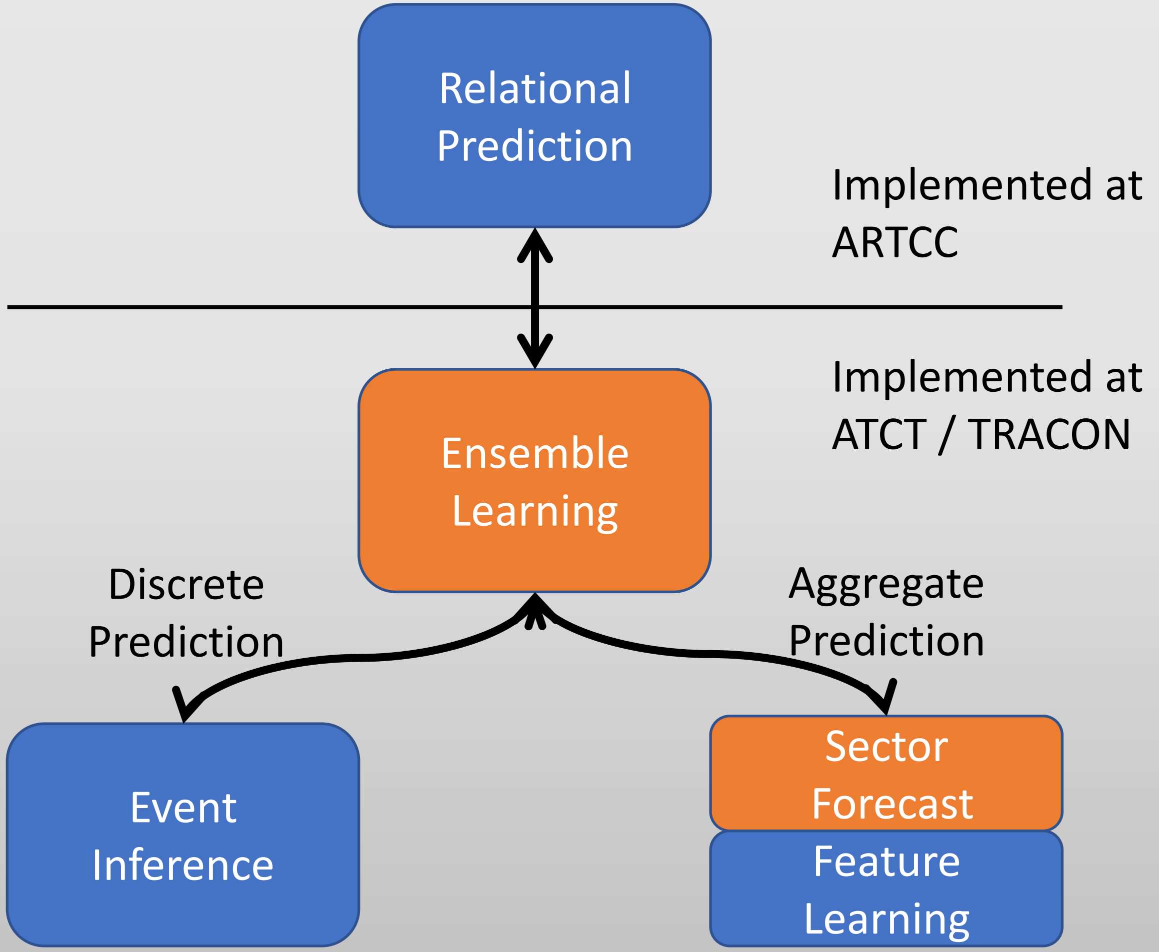
Data Engineering

Inputs		Model		Outputs
Inst counts$_{t-1}$, Avg transit time$_{d-1}$	Horizontal →	ML Model	← Horizontal	Inst counts$_{t}$ (by-phase) (Transit?)
~~Airways, ARTCCs~~ static/learned feature (Inst Counts$_{t-1}$)	Conflict →		← Conflict	Airspeed & altitude adjustments
Total sector crossing$_{d-1}$, Echo Top/CWAM, (Inst Counts$_{t-1}$), NOTAMs	Coordination →		← Coordination	Landing/Takeoff clearances, Sector Crossings
(ET/CWAM) (Inst Counts$_{t-1}$) ~~# ARTCC~~ static/learned	Altitude →		← Altitude	Altitude Adjustments (EV?)

Event Prediction

Overview and Model Interplay

- Aggregate Prediction
  - Given sector-level statistics, approximate sector demand.
  - Focus on relationships of data, learning embedded/personalized sector information
- Discrete Prediction
  - Given live flight and weather information, identify conflict and maneuvering events
  - Predictions are (theoretically) more accurate/informed than aggregate
- Relational Prediction
  - Given sector-level predictions, model how demand is displaced due to airspace events.
  - Relies on Aggregate + Discrete Predictions



Event Prediction

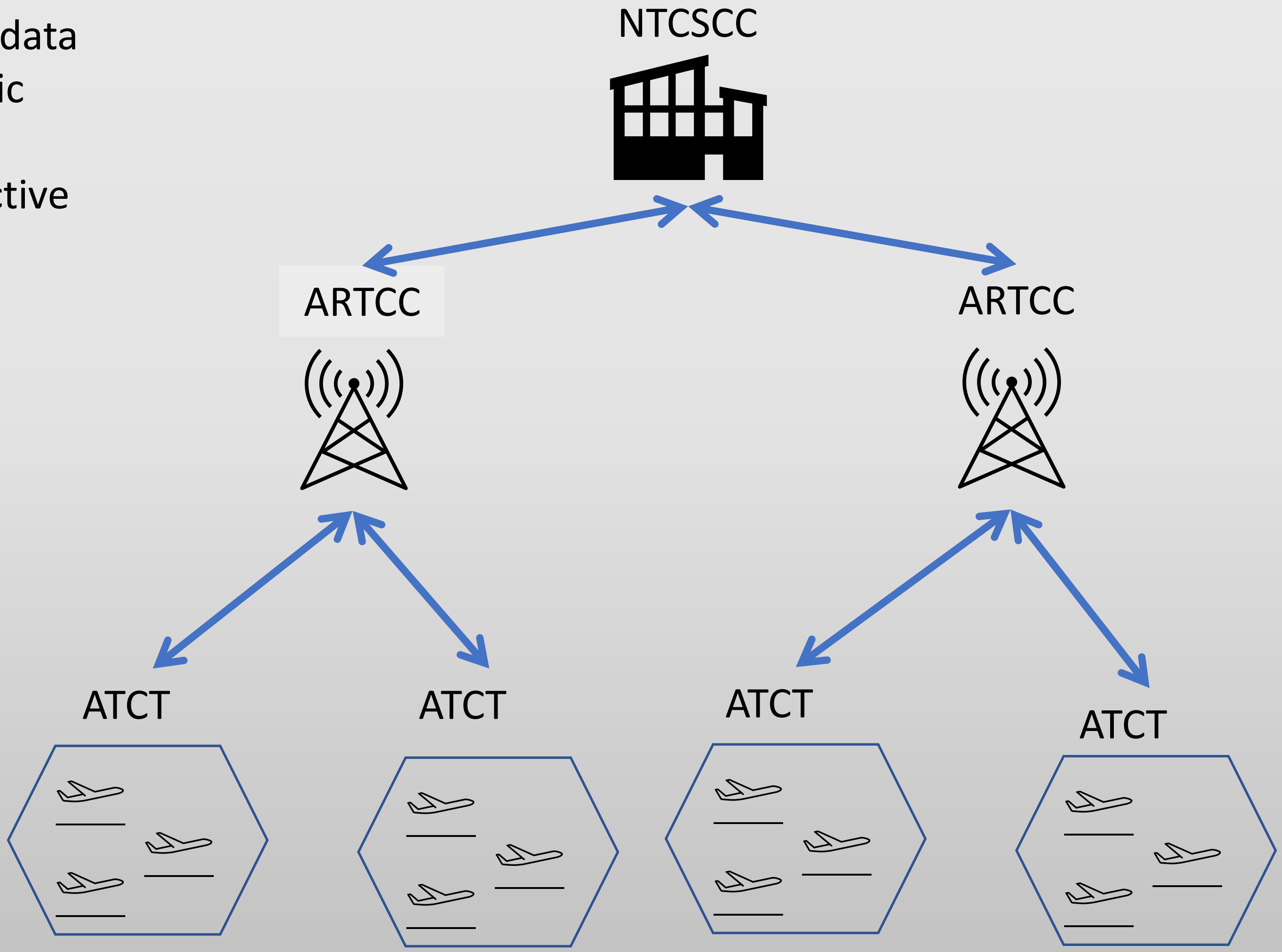
Aggregate Prediction

- Global federated learning can learn general trends in data
- Federated Personalization must identify sector-specific trends and seasonalities
- Considers “optimal” data: no outages, limited convective weather

NTCSCC: Server model for event inference
Aggregated from edge models (FedAvg)

ARTCC: Edge models for event inference
mediates sectors in evenly-distributed workload clusters (Astraea)
No additional data incorporated

ATCT/TRACON: local / client models
Inputs: density, transit time, total crossings$_{d-1}$ CWAM
Outputs: density, sector crossings, takeoff/landing clearances, airspeed/altitude adjustments



Event Prediction

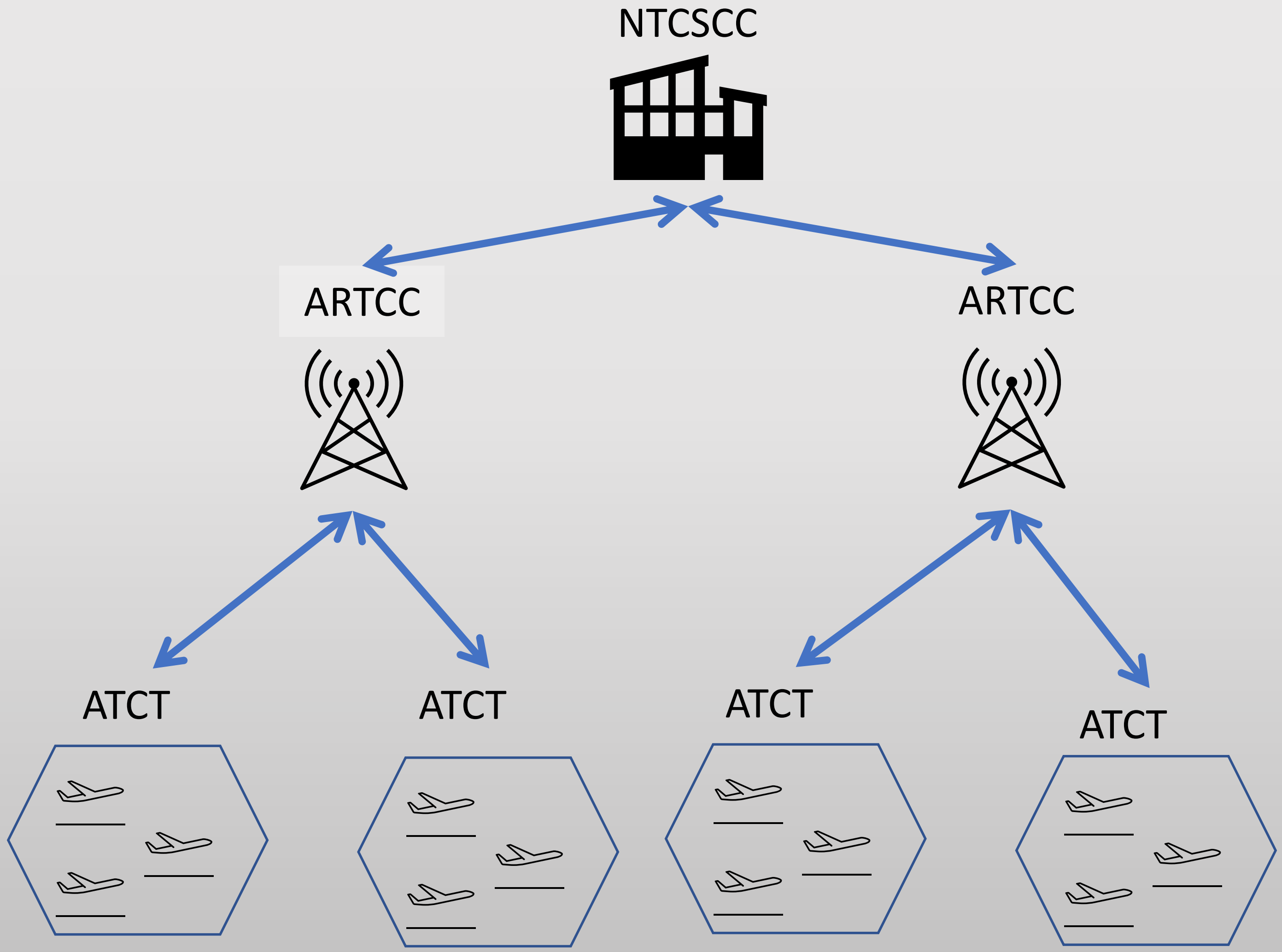
Discrete Prediction

- Global federated learning model sufficient
- No data limitations / extensive filtering necessary
- Predictions may be limited due to expected inference complexity

NTCSCC: Server model for event inference
Aggregated from edge models (FedAvg)

ARTCC: Edge models for event inference
mediates sectors in evenly-distributed workload clusters (Astraea)
No additional data incorporated

ATCT/TRACON: local / client models
Inputs: sector-coverage of ADS-B data, CWAM
Outputs: density, sector crossings, takeoff/landing clearances, airspeed/altitude adjustments



Event Prediction

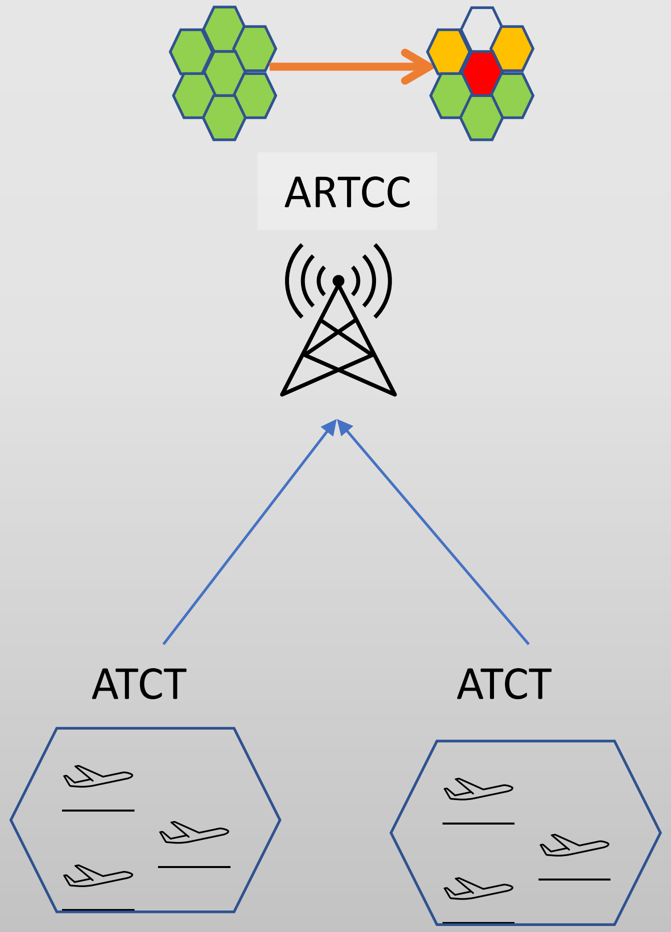
Relational Prediction

- Input predictions under nominal conditions
- Federated learning irrelevant: displacements influenced largely by region/sector structure

NTCSCC:
Potentially aggregates a global model (FedAvg)
Likely ignored – relational patterns too specific to each region

ARTCC:
Estimates offsets in demand as a result of facility / capacity limits, convective weather
Inputs: Region-coverage CWAM,
Sector-level Aggregate predictions
Outputs: Actual/displaced aggregate predictions

ATCT/TRACON:
Generates nominal-condition aggregate predictions



Parameter Inference

- Inputs: Demand events over X-minute window
- Outputs: Comm parameters (channel access duration, bandwidth, datarate, power, and modulation technique)
- Current usage estimation
  - Limited data availability: CPDLC, RWTH Aachen measurements, direct monitoring
  - Approaches:
    - Centralized v. hierarchical federated/machine learning
    - K-means clustering, KNN, linear regressions, Decision Tree variants
- Speculative: Linear model, Decision Tree with assumed weights

Conclusions

- Intelligent allocation of spectrum requires detailed knowledge of communication demand
- Communication demand must be informed by the systemwide operations of the airspace
- Modular approaches to demand prediction enable a flexible, speculative assessment of spectrum allocation schemes
- Immediate implementation work may begin with assessing these models in airspace density (a simplified case)